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A Hybrid Meta-heuristic Method for Unit Commitment Considering Flexible Charging and Discharging of Plug-in Electric Vehicles

Zhile Yang, Kang Li, Xiandong Xu

Abstract—Unit commitment is a key issue in power system operation and has long been an intractable problem due to its complex mix-integer nonlinear formulation. The original unit commitment problem aims to minimize the fossil fuel cost by determining the on/off status of power units and power contribution of each online unit at the same time. However, the uncoordinated large charging power necessity of plug-in electric vehicles brings unprecedented challenges to the power system operators and further perplexes the unit commitment problem. To seamlessly integrate the plug-in electric vehicles into the unit commitment, a new binary/real-value hybrid meta-heuristic algorithm framework is proposed in this paper, simultaneously determining the binary status and power output of units as well as the power delivered to/feedback from flexible charging and discharging of plug-in electric vehicles. A batch of binary particle swarm optimisation variants with different transfer functions are implemented and compared in solving the unit commitment problem with and without plug-in electric vehicles. Numerical studies illustrate the effectiveness of the proposed intelligent algorithm and the impact of different transfer function is evaluated.

Keywords—unit commitment; plug-in electric vehicles; binary; real-valued; transfer function

I. INTRODUCTION

Global warming due to extensive consumption of fossil fuels has been a major challenge that mankind is facing in the past decade. The global agreement forged in the most recent Paris Climate Conference set a target to limit the maximum temperature rise within 2 °C by the end of this century [1]. To achieve this goal, to reduce the green house gas (GHG) emissions from both the power generation and transportation is a key [2], and intelligent scheduling of power system for seamless integrating the electric vehicles is a promising solution.

Unit commitment (UC) is a mix-integer nonlinear NP-hard problem which requires simultaneously determining the binary on/off status of power generation units and the real valued power output of on-line units while obeying several constraints such as power limit minimum up/down time limit, power balance limit, etc. A number of studies have been conducted over the past few decades to solve the problem including conventional analytic methods, intelligent methods, and some hybrid methods. Conventional methods such as dynamic programming (DP) [3], Lagrangian relaxation (LR) [4], branch and cut (BC) [5], Benders decomposition (BD) [6], priority list (PL) [7] as well as some other mix-integer programming solvers [8] have successfully been utilised. However, the significantly

increased system complexity due to the introduction of a number of new players into the power system in recent years, such as distributed renewable generations brings considerable computational requirement on these conventional approaches, making them technically less appealing. On the other hand, intelligent mix-coded meta-heuristic algorithms such as genetic algorithm (GA) [9], harmony search (HS) [10], particle swarm optimisation (PSO) [11], firefly algorithm [12] and teaching learning based optimisation (TLBO) [13] have been employed to solve UC problems and achieved some good results. These methods however require a large number of iterations to ensure the algorithm convergence, which may reduce their computational efficiency. Hybrid algorithm frameworks combine binary meta-heuristic methods such as binary particle swarm optimisation (BPSO) [14], quantum-inspired particle swarm algorithm (QPSO) [15] and binary gravitational search algorithm (BGSA) [16] with the conventional Lagrangian relaxation method to trade off the accuracy and convergence speed. However, a large number of plug-in electric vehicles (PEVs) introduced into the power system end users and their integration with the grid through both grid-to-vehicle (V2G) and vehicle-to-grid (V2G) has brought even more remarkable challenges to the power system operators.

The PEVs are referred to pure battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), both installed with a large capacity of battery pack and requiring power injection from the grid [17]. Coordinated charging of PEVs may relieve the significant impacts of their stochastic behaviours on the grid and reduces the fossil fuel cost [18]. Further, the aggregation of PEVs forms a new type of energy storage and potential to provide vehicle to grid (V2G) ancillary services [19] and improve system reliability and resilience [20]. It is therefore crucial to intelligently coordinate the charging and discharging of PEVs from the aggregator perspective. In previous researches, PEVs are treated as integer variables [21,22] or fixed load profile [23] in the UC problem. However, future PEVs aggregators require smooth and flexible optimal charging curve for balancing the charging behaviours of multiple chargers under coordination.

In this paper, a new framework combining UC problem and real valued PEVs power output of charging and discharging, namely UCP problem, is formulated. To solve the problem, a hybrid framework is then proposed which integrates both binary and real valued meta-heuristic methods as well as lambda iteration method to simultaneously optimize mixed integer problem with different type of variables. Comparative studies considering a batch of binary particle swarm

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optimisation (BPSO) variants with 8 different probability transfer functions and the self-adaptive differential evolution (SaDE) are made.

The rest of the paper is organized as follows. The UCP problem formulation is presented in Section II, followed by the hybrid framework proposed in Section III. The detailed implementation procedure for solving the UCP problem is illustrated in Section IV. Then, numerical results of algorithm parameters study and comparisons of multiple PEVs penetration scenarios are provided and analysed in Section V. Section VI concludes the paper.

II. PROBLEM FORMULATION

A. Objective function

The objective function of the UCP problem is the economic cost of power generations, with two parts being the fossil fuel cost and the start-up cost respectively.

1) Fuel cost

$$F_{j,t}(P_{j,t}) = a_j + b_j \cdot P_{j,t} + c_j \cdot P_{j,t}^2 \quad (1)$$

$P_{j,t}$ and $F_{j,t}$ are the power and fuel cost at time t . a_j , b_j and c_j are the fuel cost coefficients of each corresponding unit.

2) Start-up cost

$$SU_{j,t} = \begin{cases} SU_{H,j}, & \text{if } MDT_j \leq TOFF_{j,t} \leq MDT_j + T_{cold,j} \\ SU_{C,j}, & \text{if } TOFF_{j,t} > MDT_j + T_{cold,j} \end{cases} \quad (2)$$

Start-up cost $SU_{j,t}$ is either cold-start cost $SU_{C,j}$ or hot-start cost $SU_{H,j}$. The minimum down time and minimum up time are denoted as MDT_j and MUT_j . $T_{cold,j}$ is the cold-start hour, and $TOFF_{j,t}$ is the off-line duration time.

It should be noted that the costs for both grid to vehicle (G2V) and V2G service are ignored in this study. The final objective cost function is therefore given below,

$$\min \sum_{t=1}^T \sum_{j=1}^n [F_j(P_{j,t}) \cdot u_{j,t} + SU_{j,t} \cdot (1 - u_{j,t-1}) \cdot u_{j,t}] \quad (3)$$

where $u_{j,t}$ denotes the binary status of on/off-line units and the start-up cost is occurred in the start-up status. The economic cost is determined by n units over T time periods.

B. Constraints

In association with the objective function, the UCP problem combines the limitations of power systems and G2V/V2G service of PEVs are also considered.

1) Generation limit

Generation limit is the maximum and minimum power generation of each unit shown as,

$$u_{j,t} \cdot P_{j,min} \leq P_{j,t} \leq u_{j,t} \cdot P_{j,max} \quad (4)$$

where $P_{j,min}$ and $P_{j,max}$ are the minimum and maximum power limits respectively.

2) Power demand limit

In the PEV-UC problem, the sum of unit generation should meet the power demand and G2V/V2G power as shown below,

$$\sum_{j=1}^n P_{j,t} \cdot u_{j,t} = P_{D,t} + P_{PEV,t} \quad (5)$$

where $P_{D,t}$ is the predicted user demand, and $P_{PEV,t}$ represents the G2V power delivered to or V2G power provided by the PEVs at time t respectively. The PEVs are either serving in G2V mode as positive real-valued of $P_{PEV,t}$ or V2G mode as negative real-valued at one time interval. Simultaneous charging and discharging are not available for the PEVs aggregator considered in this paper.

3) Power reserve limit

The spinning reserve of power system aims to provide fast response to compensate the deviations between real and predictive demands. Considering the PEVs, the new reserve limit is modelled as follows,

$$\sum_{j=1}^n P_{j,max} \cdot u_{j,t} \geq P_{D,t} + SR_t + P_{PEV,t} \quad (6)$$

where SR_t is the reserved power provided at time t . The PEVs power is accumulated in the power demand side, being demand in G2V mode and power generation in V2G mode.

4) Minimum up/down time limit

Thermal power generation units has minimum up and down time limit as shown,

$$u_{j,t} = \begin{cases} 1, & \text{if } 1 \leq TON_{j,t-1} < MUT_j \\ 0, & \text{if } 1 \leq TOFF_{j,t-1} < MDT_j \\ 0 \text{ or } 1, & \text{otherwise} \end{cases} \quad (7)$$

where the unit is required to turn on or off within minimum periods.

5) Charging/Discharging power limit

In supporting the daily use, a certain amount of power should be injected into the PEVs batteries. It is therefore necessary to limit the accumulated charging/discharging power denoted as follows,

$$\sum_{t=1}^T P_{PEV,t} = E_{EV,total} \quad (8)$$

The energy necessity $E_{EV,total}$ is the total power that needs to be charged for the PEVs in a one day time horizon. In the UCP problem, PEVs are able to provide both charging and discharging services and the maximum charging and discharging power boundary is limited as follows:

$$P_{EVD,t,max} \leq P_{PEV,t} \leq P_{EVC,t,max} \quad (9)$$

where the $P_{EVD,t,max}$ and $P_{EVC,t,max}$ is the discharging and charging power boundary respectively. In some studies [21, 22], the

charging and discharging power of PEVs is dispatched by the number of PEVs and multiplied with the corresponding charging/discharging ability. In real-life applications, the power charging and discharging capacity of PEVs is specific in the vehicle model, due to which it is not proper to directly dispatch the number. An intelligent PEVs aggregator is assumed to balance the charging and discharging behaviours of each PEV according to a real-valued desired curve in this paper. In the UCP problem formulation, this optimal desired power curve of PEVs will be provided. The complicated UCP problem calls for powerful computational techniques to determine the binary and real-valued decision variables in the formulation.

III. BINARY/REAL-VALUED PARALLEL META-HEURISTIC METHOD

In this section, a new hybrid binary/real-valued meta-heuristic method is proposed combining binary particle swarm optimisation, real-valued self-adaptive differential evolution method and lambda iteration method to simultaneously determine the unit commitment and PEV power distribution in a day-ahead power system scheduling horizon.

A. Binary particle swarm optimisation

Particle swarm optimisation is one of the most popular meta-heuristic algorithms and has been utilized in solving many power system problems [24]. The original binary PSO has been employed in some early researches [21] in association with integer PSO to determine the on/off status of units and the power of PEVs. The PSO algorithm mimics a swarm of particles adjusting their positions according to an updated velocity denoted as follows.

$$v_i(t+1) = w(t) \cdot v_i(t) + c_1(t) \cdot rand_1 \cdot (p_{lbest,i} - x_{bi}(t)) + c_2(t) \cdot rand_2 \cdot (p_{gbest} - x_{bi}(t)) \quad (10)$$

where $v_i(t+1)$, $v_i(t)$ and $x_{bi}(t)$ are the updated velocity, current velocity and the binary variable of the i^{th} binary particle at t^{th} iteration. $w(t)$, $c_1(t)$ and $c_2(t)$ represent the weighting, social and cognitive coefficients respectively. $p_{lbest,i}$ and p_{gbest} are the binary local and global best solutions. Two random numbers ranging from 0 to 1 are denoted as $rand_1$ and $rand_2$ respectively. The binary variables are determined by a sigmoid-shape probability transfer function shown as follows,

$$P(v_i(t+1)) = \frac{1}{1 + e^{-v_i(t+1)}} \quad (11)$$

where the $P(v_i(t+1))$ represents the probability and the value will be compared with a random number $rand_3$ to determine the binary variable as shown below.

$$x_{bi}(t+1) = \begin{cases} 1, & \text{if } rand_3 < P(v_i(t+1)) \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

The performance of BPSO highly depends on the probability transfer function, due to which the original transfer function sees slow convergence speed in optimizing some specific problems [25,26]. To remedy this drawback, V-shape transfer functions have been utilized in solving some unit commitment studies [27,28]. The probability is redesigned as V-shape where an absolute value operator is utilized to convert the probability distribution P to be symmetric. In this paper, 8 variants of

binary PSO with a family of transfer functions shown in Table 1 are utilized respectively in the parallel method to compare the impact of binary transfer function on the unit commitment results.

Table 1. Binary transfer functions for proposed hybrid method

S-shape family		V-shape family	
Name	Transfer function	Name	Transfer function
T1	$P(x) = \frac{1}{1 + e^{-x}}$	T5	$P(x) = \left \operatorname{erf}\left(\frac{\sqrt{\pi}}{2}x\right) \right $
T2	$P(x) = \frac{1}{1 + e^{-2x}}$	T6	$P(x) = \tanh(x) $
T3	$P(x) = \frac{1}{1 + e^{\left(\frac{x}{-2}\right)}}$	T7	$P(x) = \left (x)/\sqrt{1+x^2} \right $
T4	$P(x) = \frac{1}{1 + e^{\left(\frac{x}{-3}\right)}}$	T8	$P(x) = \left \frac{2}{\pi} \arctan\left(\frac{\sqrt{\pi}}{2}x\right) \right $
$x_{bi}(t+1) = \begin{cases} 1, & \text{if } rand_3 < P(x) \\ 0, & \text{otherwise} \end{cases}$		$x_{bi}(t+1) = \begin{cases} x_{bi}(t), & \text{if } rand_3 < P(x) \\ 1 - x_{bi}(t), & \text{otherwise} \end{cases}$	

In Table 1, the left side columns are the S-shape family of which the binary variables are determined as '1' if the probability exceed a random number, while they keep the original value in the same case and turns to the complementary status if the probability is smaller.

B. Self-adaptive differential evolution

Differential evolution (DE) is another popular heuristic optimization method and has also been widely used in various applications and engineering fields [29]. Two key phases are employed in DE namely mutation and crossover. The original DE has the advantage in exploitation, but its weakness is the convergence speed. To overcome this drawback, the self-adaptive differential evolution [30] is adopted to optimize the PEV charging/discharging power where two different DE variants, namely rand/1/bin and current to best/2/bin are introduced. The selection of the variants is determined by the probability p_s .

The mutation process of SaDE is denoted as follows:

$$V_{i,G} = \begin{cases} X_{r1,G} + F \cdot (X_{r2,G} - X_{r3,G}), & \text{if } p_s < p_1 \\ X_{i,G} + F \cdot (X_{best,G} - X_{i,G}) + F \cdot (X_{r1,G} - X_{r2,G}), & \text{otherwise} \end{cases} \quad (13)$$

where $V_{i,G}$ represents the mutation vector of the i^{th} particle in the population at G^{th} iteration and F is the mutation factor. $X_{r1,G}$, $X_{r2,G}$, $X_{r3,G}$, $X_{best,G}$ and $X_{i,G}$ denotes the three random particles $r1$ - $r3$, the best particle so far and the i^{th} particle in the whole population at G^{th} iteration. When the determined probability p_s is less than p_1 , the rand/1/bin is selected, and the current to best/1/bin variant is selected vice versa. The p_1 is calculated as follows:

$$p_1 = \frac{ns_1 \cdot (ns_2 + nf_2)}{ns_2 \cdot (ns_1 + nf_1) + ns_1 \cdot (ns_2 + nf_2)} \quad (14)$$

where ns_1 and ns_2 denote the number of trail vectors that have been adopted by the next generation of both variants while the

nf_1 and nf_2 represent the failure times. The trail vectors are generated by a crossover operation and as shown below,

$$u_{j,i,G} = \begin{cases} v_{j,i,G}, & \text{if } rand_4 < CR \text{ or } j = j_{rand} \\ x_{j,i,G}, & \text{otherwise} \end{cases}, \quad j = 1, 2, \dots, n \quad (15)$$

with the $u_{j,i,G}$, $v_{j,i,G}$ and $x_{j,i,G}$ representing the trail vector, mutation vector and original vector of j^{th} position in the i^{th} particle of G^{th} iteration respectively. The mutation vector is adopted as part of the trail vector when a random number, $rand_4$ is less than crossover rate CR . The selection operation aims to determine whether to adopt the trail vector for the algorithm and it is denoted as follows,

$$X_{i,G+1} = \begin{cases} U_{i,G}, & \text{if } f(U_{i,G}) < f(X_{i,G}) \\ X_{i,G}, & \text{otherwise} \end{cases} \quad (16)$$

The corresponding number in the equation (16) will be modified according to the adoption of this operation. It should be noted that the variables in the conventional DE method are continuous real-valued.

C. Hybrid meta-heuristic method

The binary solver BPSO and real-valued solver SaDE are hybridized and provide solutions for lambda iteration method to solve the economic load dispatch shown as Fig 1.

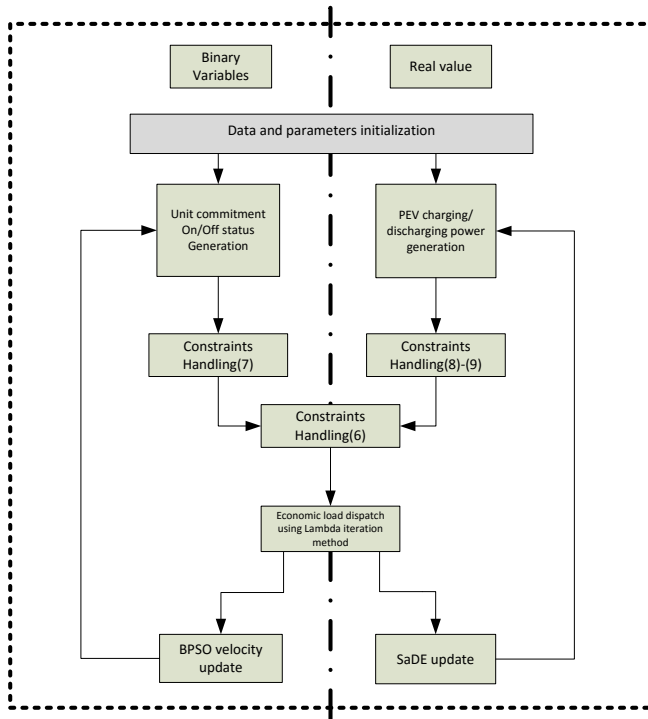


Fig.1 Flowchart of the hybrid meta-heuristic method

The detailed procedure is demonstrated as follows.

1) Initialization

All the power system data such as maximum and minimum generation power, cost coefficients, minimum up/down time, start-up cost as well as PEV data including maximum charging power, total energy necessity are imported. Algorithm parameters are initialized respectively.

2) Generate new solutions

A new set of solutions are generated in this step for both binary and real value variables. The binary variables denoting the on/off status of units are generated based on (10)-(12) while the PEV variables are updated based on the initialisation values or updated values from the previous iteration according to (13)-(16).

3) Constraints handling

Power unit constraints and PEVs constraints are handled in this step to adjust the initial solutions obtained in step 2. It should be noted that due to the participation of PEVs, some constraints are coupled in both the binary and real valued optimization processes. A hybrid handling process is therefore implemented in the proposed algorithm. The minimum up/down time limit (7) is first handled by a heuristic-based method proposed in [15] where the violation is avoided by heuristic check. Then, PEVs limits (8)-(9) are handled in the real value optimization procedure. Finally, the coupled constraint lies on the power reserve limit (6), where the commit and de-commit decisions are made depends on the heuristic check. These decisions take both binary on/off status of units and the charging/discharging power of PEVs into account at the same time.

4) Economic load dispatch

According to the decision variables adjusted by Step 3, a lambda iteration method [4] is applied to solve the economic load dispatch (ELD) sub-problem. Generation power of online units are determined with the limits (4) and (5) being relaxed. Based on the results of ELD, the values of fitness function (3) are calculated.

5) Algorithm updates

The optimal results of the fitness function achieved from Step 4 are utilized to update the probability in BPSO according to (12) and solutions by SaDE based on (16). The process goes back to Step 2 until the maximum iteration number is achieved.

IV. NUMERICAL ANALYSIS

In this section, the proposed hybrid algorithm is applied to solve 2 different case studies of the UCP problem. In Case 1, the algorithm is tested in an original 10-unit commitment problem to illustrate the impact of transfer functions on the scheduling results of the UC problem without PEVs. 8 variants of BPSO are implemented respectively and the results are analyzed. Then, the algorithm is evaluated on UCP problem considering flexible charging and discharging of PEVs. The proposed algorithm was implemented in the MATLAB® 2014a on an Intel i5-3470 CPU at 3.20GHz and 4GB RAM personal computer.

A. Case 1 10-unit only

In this case, the binary algorithms with a batch of transfer functions are comparatively studied in the original 10-unit benchmark system and the system data can be found in [31]. The best, worst and mean optimal results of hybrid PSO (HPSO) [31], QPSO [15], BGSA [32], GA-LR method [22] and binary-real-coded GA (brGA) [33] are listed in Table 2 to comparatively study the performance of the proposed method. The $w(t)$ of BPSO inertially decreases from 0.9-0.4, and $c_1(t)$ and $c_2(t)$ are equally set as 2. Each method runs 30 trials to eliminate the randomness. BPSO 1-4 are the S-shape variants in the left column of Table 1 and the BPSO 5-8 are V-shape variants. The number of particles and the maximum iteration of the BPSO are empirically set as 20 and 200 respectively to trade off the computational cost and refinement ability.

Table 2. Simulation results in Case 1

Method	Cost (\$/day)		
	Best	Worst	Mean
HPSO[31]	563,942	565,785	564,772
QPSO[15]	563,977	563,977	563,977
BGSA[32]	563,937	564,241	564,031
GA-LR[22]	—	—	564,703
brGA[33]	563,938	564,253	564,088
BPSO1	563,938	564,126	564,009
BPSO2	563,938	563,997	563,961
BPSO3	563,938	564,993	564,461
BPSO4	564,286	565,547	564,958
BPSO5	564,018	564,900	564,425
BPSO6	563,987	564,743	564,309
BPSO7	563,977	565,159	564,588
BPSO8	563,938	565,749	564,851

It could be observed from Table 2 that the BPSO variants 1-3 and 8 achieve the best results respectively as 563,938 \$/day, which is the state-of-the-art best result according to the latest publications. Moreover, the BPSO2 outperforms all the other variants as well as the previous studies in terms of mean value as 563,961 \$/day. The BPSO 5-8 show worse performance in best, mean and worst results. The S-shape transfer function based variants outperform the V-shape variants to a great extent. This is due to the fact that the fast convergence speed may cause pre-mature in the strongly constrained UC problem. The evolution processes of the 8 BPSO variants are illustrated in Fig.2. It could be observed that the V-shape based variants converge extremely fast within 5-10 iterations, whereas the S-shape based variants only converge from 25-60 iterations.

It should also be noted that the average computational time for the optimisation by the 8 variants is 36.6 seconds which is similar to the counterpart method [28]. The 8 variants of BPSO will be further combined in the hybrid method to solve the UCP problem and evaluated with the real-valued methods.

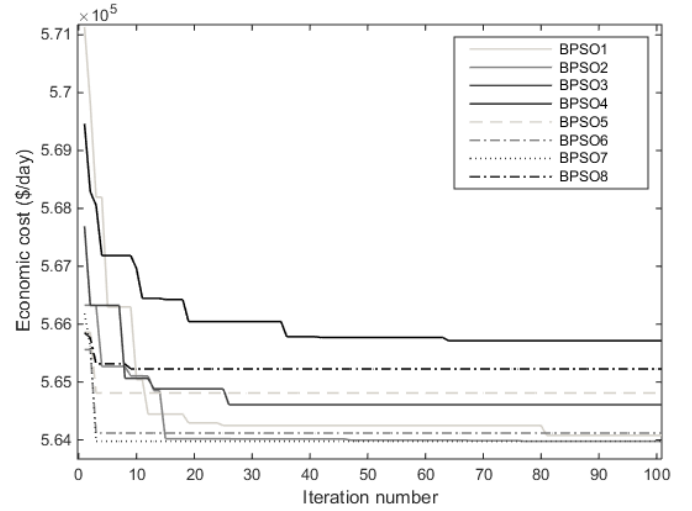


Fig.2 Iteration process of 8 BPSO variants on UC problem

B. Case 2 10-unit with PEVs charging and discharging

The UCP problem provides optimal profiles to PEV aggregator for flexible charging and discharging. The power system data and optimization parameters are the same as Case 1. Similarly, 50000 PEVs with 15KWh battery in each vehicle are adopted to integrate into the 10 unit system and 50% SOC of the batteries are assumed to be the maximum charging rate and 85% charging/discharging efficiency are assumed. The limit of charging and discharging power is assumed as 20% of the total battery number [22]. The maximum charging/discharging power is calculated as $15\text{KWh} \times 50000 \times 50\% \times 85\% \times 20\% / 1\text{h} = 63.75\text{ MW}$. Moreover, According to the National Household Travel Survey [34], the average daily travel distance for a vehicle is 32.88 miles. An energy necessity of 8.22 kWh is therefore required to support this, and the total energy necessity of PEVs is calculated as $50,000 \times 8.22\text{kWh} = 411\text{MWh}$. The cross over rate CR and mutation rate F of SaDE method are tuned from 0.1 to 0.9 respectively associated with the BPSO2 variant as illustrated in Table 3.

Table 3. Results achieved for parameter tuning (\$/day)

	F=0.1	F=0.2	F=0.3	F=0.4	F=0.5	F=0.6	F=0.7	F=0.8	F=0.9
CR=0.1	568,239	568,275	567,214	566,536	566,657	566,223	566,341	566,347	565,922
CR=0.2	569,078	567,456	567,192	565,752	566,294	566,386	566,078	566,127	566,118
CR=0.3	568,369	568,300	566,939	566,570	566,516	566,234	565,904	566,069	566,054
CR=0.4	568,683	567,688	566,958	566,726	566,120	566,225	566,249	566,066	566,228
CR=0.5	568,771	568,657	567,549	566,515	566,153	566,081	566,125	566,281	566,258
CR=0.6	568,351	568,475	566,621	567,120	566,086	566,045	565,502	566,104	566,031
CR=0.7	568,998	569,265	567,747	566,883	566,391	566,178	566,255	566,318	566,129
CR=0.8	569,403	568,165	568,029	566,967	566,107	566,214	566,094	566,278	566,336
CR=0.9	567,730	568,335	567,285	567,629	566,203	565,912	566,209	566,124	566,465

It could be observed that the best parameter combination is $F=0.7$ and $CR=0.6$ with the value as 565,502 \$/day. This optimal combination is then utilized in the evaluation of the impact of transfer function on the economic cost of Case 2. The 8 BPSO variants are implemented in the hybrid parallel method together with SaDE under the same parameter settings and the results are shown in Table 4. In addition, the original rand/1/bin DE with the same crossover and mutation rate is implemented to compare the performance of real-valued SaDE.

Table 4. Case 2 Results of BPSO variants families

Method	Cost (\$/day)		
	Best	Worst	Mean
BPSO2+DE	566,700	567,671	567,246
BPSO1+SaDE	566,405	567,924	567,275
BPSO2+SaDE	565,502	567,073	566,620
BPSO3+SaDE	567,261	569,649	568,406
BPSO4+SaDE	568,013	569,648	568,823
BPSO5+SaDE	567,746	569,751	568,771
BPSO6+SaDE	567,783	570,127	569,137
BPSO7+SaDE	567,961	570,800	569,652
BPSO8+SaDE	568,629	571,775	570,274

It could be seen from the Table 4 that the BPSO2 variant associated with SaDE shows remarkable performance in best, worst and mean results compared with all the counterparts in this case. The best result achieved by BPSO2 based hybrid method is 565,502 \$/day, which has a less cost of 1,000 to 2500 \$/day comparing with other BPSO variants based methods, and a more cost of 1,100 \$/day comparing with UC-only result. Moreover, SaDE algorithm has a priori performance compared with original DE algorithm parallel operated with the same variant BPSO2, with a 1,200 \$/day cost reduction. Fig.3 illustrates the distribution of optimal results achieved by all the hybrid method based on 8 BPSO variants.

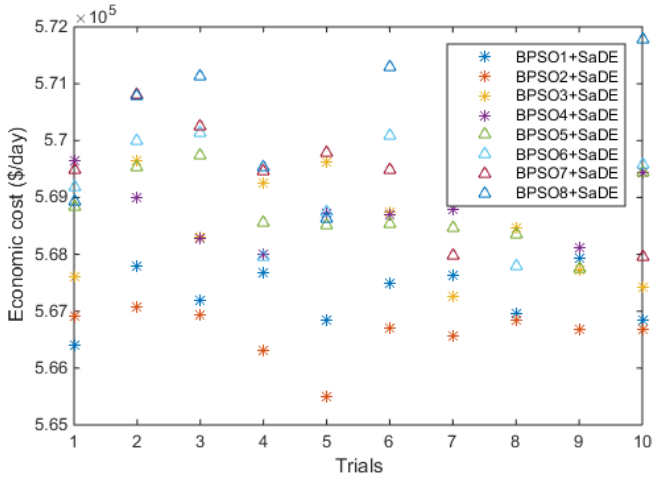


Fig.3 Distribution of Optimal results of algorithm for Case 2

In Fig.3, the S-shape based hybrid methods are illustrated in star marks while the V-shape based methods are shown in triangle marks. The figure clearly shows that the majority of S-shape based methods outperform the V-shape based method and the BPSO2 based method performs the best in 9 out of 10 trials.

The comparative study shows that the proposed hybrid based meta-heuristic method has remarkable performance in solving UCP problem, simultaneously determine the binary and real-valued power system variables and real-valued PEVs variables. The impact of transfer functions on the system cost is evaluated and BPSO2 turns out to be the best performed variant.

V. CONCLUSION AND FUTURE WORK

In this paper, flexible charging and discharging of PEVs is integrated in the unit commitment problem, namely the UCP problem. A new hybrid parallel meta-heuristic method is proposed to solve the problem, combining the binary PSO, SaDE and lambda iteration method, where 8 variants of PSO with different transfer functions are employed respectively and analyzed. The results demonstrate the effectiveness of the hybrid method in solving the UCP problem, and the selection of transfer functions has noticeable impact on reducing the economic cost both with and without the integration of PEVs.

With the fast development of smart grid, high penetration of intermittent undispachable renewable energy generation and dispatchable distributed load and generations such as plug-in electric vehicles and energy storage systems significantly perplex the system scheduling. Future work will be addressed in developing new algorithms to solve the large scale mix-integer constrained UCP problem. The integration of uncertain renewable energy generation and multiple penetrations of PEVs are also worth investigation.

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